



Optimization project:

Modeling and Optimization of Cement Raw Materials Blending Process



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This project focuses on modelling and solving the ingredient ratio optimization problem in cement raw material blending process. A linear model and a general nonlinear time-varying (G-NLTV) model are established for cement raw material blending process via considering chemical composition, feed flow fluctuation, and various craft and production constraints. Different objective functions are presented to acquire optimal ingredient ratios under various production requirements. The ingredient ratio optimization problem is transformed into discrete-time single objective or multiple objectives rolling nonlinear constraint optimization problem.

This paper is arranged as follows:

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1-Introduction :

Cement is a widely used construction material in the world. Cement production will experience several procedures which include raw materials blending process and burning process, cement clinker grinding process, and packaging process. Cement raw material and cement clinkers mainly contain four oxides: calcium oxide or lime (CaO), silica (SiO_2), alumina (Al_2O_3), and iron oxide (Fe_2O_3). The cement clinkers quality is evaluated by the above four oxides. Hence, ingredient ratio of cement raw material will affect the quality

and property of cement clinker significantly. Optimal ingredient ratio will promote and stabilize cement quality and production craft. Therefore, cement raw materials should be reasonably mixed. Hence, it is a significant problem to obtain optimal ingredient ratio. The first step in applying an adaptive and dynamic control strategy to this kind of process is obtaining an appropriate mathematical model of the process. This paper is concerned with modeling the raw-material blending process in cement industry by using neural networks.

Linear and **Nonlinear** Neural Network models were developed and the results were compared with the experimental data.

2-Neural network models:

Artificial neural networks are forecasting methods that are based on simple mathematical models of the brain. They allow complex nonlinear relationships between the response variable and its predictors.

A neural network can be thought of as a network of “neurons” which are organized in layers. The predictors (or inputs) form the bottom layer, and the forecasts (or outputs) form the top layer. There may also be intermediate layers containing “hidden neurons.”

The simplest networks contain no hidden layers and are equivalent to linear regressions. Figure 1 shows the neural network version of a linear regression with four predictors. The coefficients attached to these predictors are called “weights.” The forecasts are obtained by a linear combination of the inputs. The weights are selected in the neural network framework using a “learning algorithm” that minimizes a “cost function” such as the MSE. Of course, in this simple example, we can use linear regression which is a much more efficient method of training the model. Once we add an intermediate layer with hidden neurons, the neural network becomes non-linear. A simple example is shown in Figure 2.

The neural network without any activation function is any of its layers is called neural network.

 **The neural network which has action functions like the ReLU activation function, sigmoid or tanh is any of its layer or even in more than one layer is called non-linear neural network.**

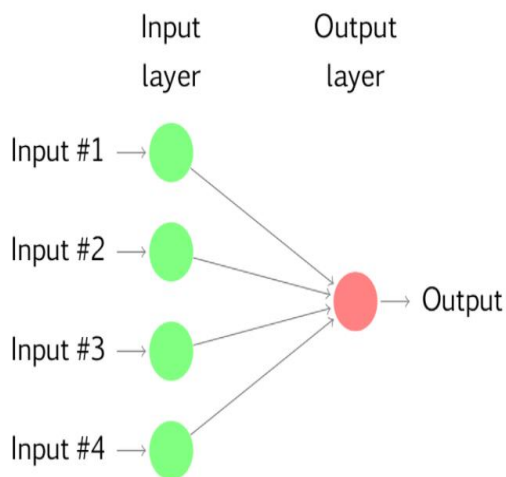


Figure 1: A simple neural network

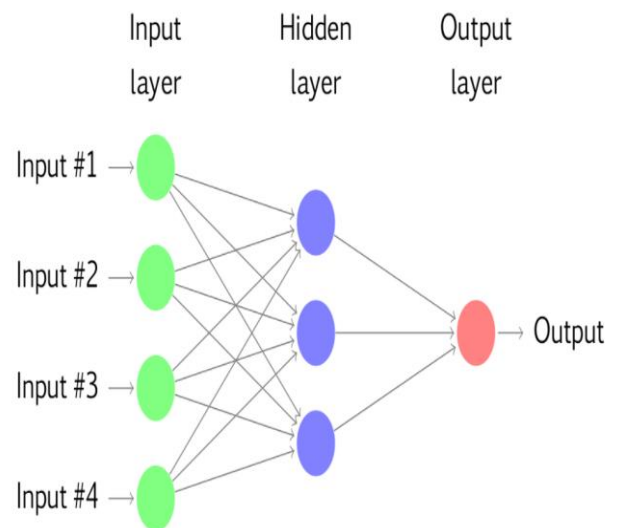


Figure 2: A neural network with four inputs and one hidden layer with three hidden neurons.

3-Cement raw-material blending process:

Limestone: Contains predominantly calcium carbonate (CaCO_3) and to use in cement manufacture, it should have 42-43% lime (CaO) minimum. In cement manufacture it is prime raw material and its usage would be 90- 93%.

Clay: It contains more of silica (SiO_2) and its usage should be 2 to 3% in cement manufacture.

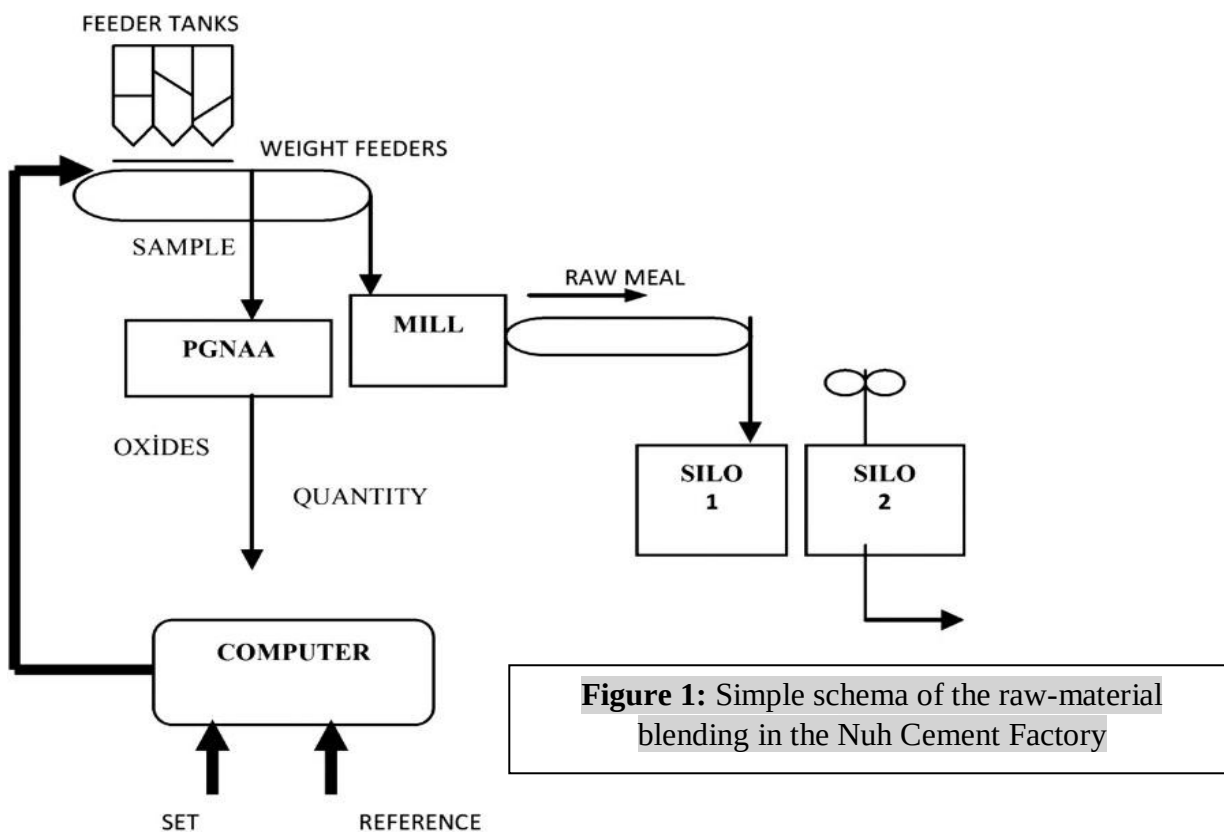
Bauxite: It contains alumina (Al_2O_3) and it's usage should be 2 to 3% in cement manufacture.

Iron Ore: It contains mainly iron oxide (Fe_2O_3) and it's usage should be 1 to 2% in cement manufacture. The raw materials mix composition would be 90-93% limestone, 2- 3% clay, 2-3% Bauxite, 1-2% Iron ore in cement making.

Fuel: Coal is used for burning the raw mix in powdered form. Normally both imported and indigenous coal are used, coal is being imported from mainly South Africa, Australia etc. because of low ash content. Pet coke is also used as alternate fuel while manufacturing of cement.

4-Cement raw-material blending process:

The cement -manufacturing process consists broadly of mining, crushing and grinding, burning, and grinding with gypsum. In the dry process of cement production, the raw materials are proportioned, stored, ground, mixed, pulverized, and fed into the kiln in a dry state. Inside the kiln the raw mix will undergo a sequence of reactions. Sintering takes place at the final stage of the reaction, i.e., at 1400–1450 °C, and a substance called clinker, having its own physical and chemical properties, is formed. The clinker is cooled, crushed, and mixed with a predetermined percentage of gypsum to regulate the setting time of the cement. Finally, the finished product, known as Portland cement, is stored in large storage bins called silos, from which it is fed to an automatic packing machine.



The original cement materials are obtained from a natural mine, thus the chemical composition is time varying function. Composition fluctuation is inevitable and it may contain randomness. Therefore, modeling of the cement raw-material blending process becomes more important and a challenge.

In this study, the raw material blending process in the Nuh Cement Factory in Turkey was investigated. Here, three different feed streams, which are low grade, high grade and iron ore, are controlled by weigh feeders and, after mixing on a conveyor belt, fed to the raw mill. A simplified schematic diagram of the raw mill blending process is shown in **Figure 1**.

Mixing on a conveyor belt is fed to the raw mill by weight-feeders, before being thoroughly ground and mixed in the raw mill. In this study, two feed streams containing low grade and iron ore were modeled, because the values of all the measurements are a percentage. A sample of this raw mix is collected at the input of the raw mill grinder by an auto sampler and analyzed every five seconds and the average of twelve analyses is sent to the computer through a data-communication line by PGNA (Prompt Gamma Neutron Activation Analyzers). These data are utilized and manipulated for the raw meal feed stream. Thus, the desired blend is supplied continuously. The measurements consist of the output concentrations of the four basic oxides (CaO, SiO₂, Fe₂O₃ and Al₂O₃). The raw meal is transferred to homogenization basins where further continuous mixing decreases the magnitude of the concentration variations about the silo average values. The complete filling of a basin requires a unit batch time of 16h .

The quality of raw meal depends on the relative rates of CaO, SiO₂, Fe₂O₃ and Al₂O₃. The relative rates can be expressed by the so-called modulus values: Lime standard (or modulus):

Lime standard (or modulus):

$$ML = \frac{100\text{CaO}}{2.8\text{SiO}_2 + 1.1\text{Al}_2\text{O}_3 + 0.8\text{Fe}_2\text{O}_3} \quad (1)$$

Aluminum modulus:

$$MA = \frac{\text{Al}_2\text{O}_3}{\text{Fe}_2\text{O}_3} \quad (2)$$

Silica modulus:

$$MS = \frac{\text{SiO}_2}{\text{Al}_2\text{O}_3 + \text{Fe}_2\text{O}_3} \quad (3)$$

A high *ML* requires a high heat consumption for the clinker burning inside the kiln and thus gives more strength to the cement. A higher *MS* decreases the liquid-phase content, which impairs the burn ability of the clinker and reduces the cement

setting time. The value of MA determines the composition of the liquid phase of the clinker. The goal is to achieve a desired level of ML , MS and MA of the raw mix, to produce a particular quality of the cement by controlling the mix proportions of the raw materials. To achieve an appropriate raw mix proportion is very difficult due to the inconsistencies in the chemical composition of the raw material.

5-Artificial neural network approach:

The Artificial Neural Network (ANN) has been developed by a generalization of the mathematical model of the human brain's ability and neural biology. The ANN, which is relatively new modeling technique, has shown remarkable performance when used to model complex linear and non-linear relationships. Neural Networks (NN) have been successfully applied to model complicated processes in many engineering applications: electronics, manufacturing, robotics, materials science and physical metallurgy, automotive, defense, and telecommunications. An ANN is a set of processing elements, or neurons, and connections with adjustable weights. A multi-layer neural network consists of an input layer, one or more hidden layers, and an output layer. The input layer is the first layer and accepts symptoms, signs, and experimental data. The layers that are placed between the input and output layers are called hidden layers. The hidden layer processes the data it receives from the input layer, and sends a response to the output layer. The output layer accepts all the responses from the hidden layer and produces an output vector. **Figure 2** shows the structure of the ANN.

Each layer has a certain number of processing elements that are connected by links with adjustable weights. These weights are adapted during the training process, most commonly through the backpropagation algorithm, by presenting the neural network with examples of input-output pairs exhibiting the relationship the network is attempting to learn.

The total input to the layer neuron i , x_i , is the summation of the weight (w_{ij}), which is associated with the connection between the neuron i and the neuron j ,

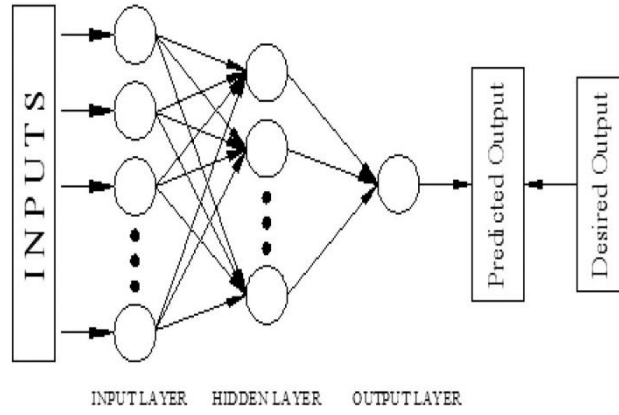


Figure 2: The structure of the ANN

multiplied by the input value received from the preceding layer neuron, x_j , for each

connection path:

$$x_i = w_{i0} + \sum_{j=1}^N w_{ij} \times x_j$$

where N is the number of inputs, w_{i0} is the bias of the neuron.

The output from neuron i , V_i , is given by: $V_i = f(x_i)$

where f is the activation function.

During training, Q sets of input and output data are given to the neural network. An iterative algorithm adjusts the weights so that the outputs (y_k) according to the input patterns will be as close as possible to their respective desired output patterns (d_k). Considering a neural network with K , which is the total number of outputs, the Mean Squared Error (MSE) function is to be minimized:

$$MSE = \frac{1}{Q \cdot K} \cdot \sum_{q=1}^Q \sum_{k=1}^K [d_k(q) - y_k(q)]^2$$

The backpropagation algorithm is the most widely used to minimize MSE by adjusting the weights of the connection links. The equation for calculating the updated weights and bias is: $w_{ijt+1} = w_{ijt} + \Delta w_{ijt+1}$

Where Δw_{ijt+1} is the ($\pm$) incremental change in the weight. The weight change is determined by an optimization method.¹³

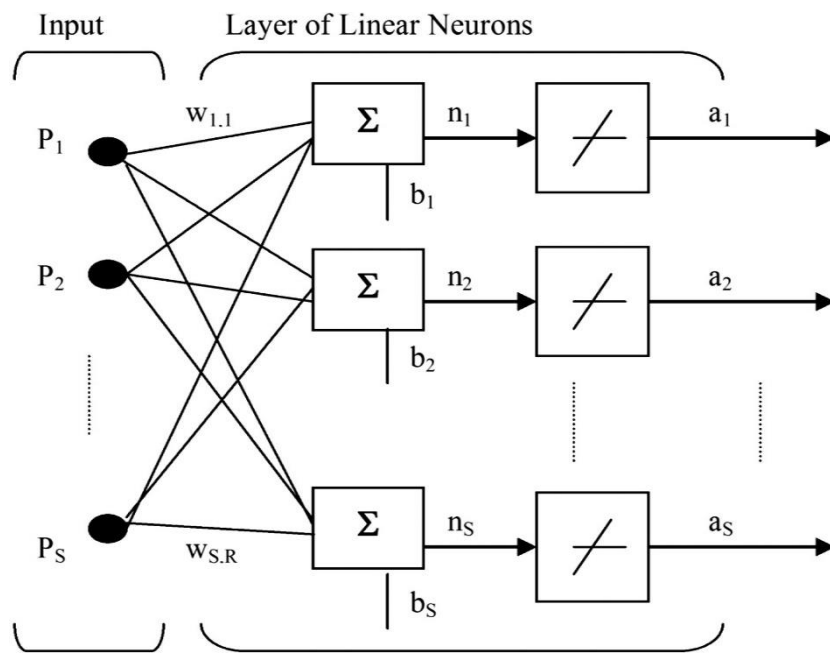


Figure 3: The linear network structure.

6-ANN Model:

Linear and Nonlinear Neural Network models were developed for the raw-material blending process in cement manufacture. The inputs of both the models are low grade and iron ore, and the outputs are Fe_2O_3 and Lime Modulus.

6.1 Linear ANN:

The linear network (ADALINE network) shown in **Figure 3** has one layer of S neurons connected to R inputs through a matrix of weights W .

The linear network has the same basic structure as the perceptron network. The only difference is that the linear neuron uses a linear transfer function. This transfer function is shown in **Figure 4**. The linear transfer function calculates the neuron's output by simply returning the value passed to it. This neuron can be trained to learn an affine function of its inputs, or to find a linear approximation to a nonlinear function. A linear network cannot, of course, be made to perform a nonlinear computation.

A nonlinear relationship between the inputs and the targets cannot be represented exactly by a linear network. Under some circumstances, backpropagation might be a good alternative.

6.2 Nonlinear ANN

The nonlinear network is shown in **Figure 5**. In this study a feed-forward backpropagation network was designed. A log-sigmoid transfer function was used

in a hidden layer and the output layer. Because, generally, a natural incident resembles the structure of a log-sigmoid function, using this function has given better results. A log-sigmoid transfer function is shown in **Figure 6**.The inputs to the system determine the neuron number in the input layer of the network and its outputs determine the neuron number in output layer of network. Eight neurons were used in the hidden layer of the model.

A neural network requires that the range of the both input and output values should be between 0.1 and 0.9

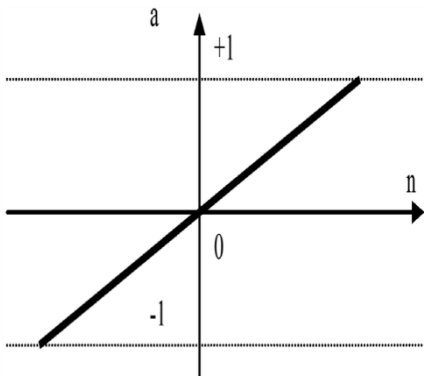


Figure 3 : Linear Transfer function

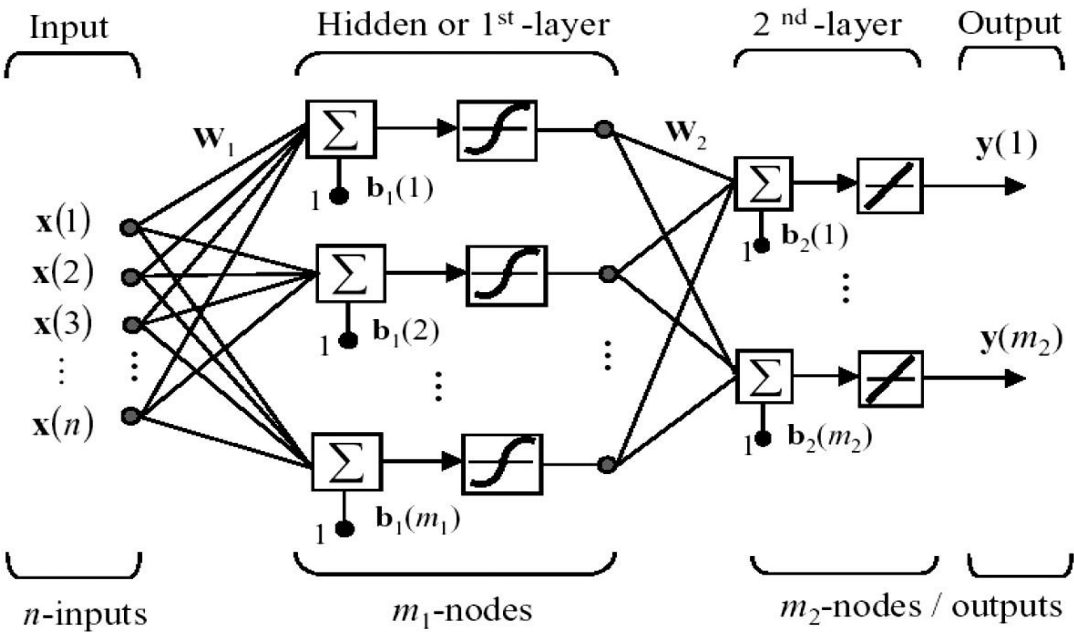


Figure 4 : the nonlinear network structure

due to the restriction of the sigmoid function, consequently, the data must be unified.

$$\text{Normalize data} = \frac{\text{actual value} - \text{minimum value}}{\text{Maximum value} - \text{minimum value}} \times (\text{High} - \text{Low}) + \text{Low}$$

is a widely employed method in unification.

In this study, the backpropagation network training function updates the weight and bias values according to the Levenberg-Marquardt optimization. The performance index was determined by the mean squared error. The Levenberg-Marquardt algorithm is very well suited to neural network training where the performance index is the mean squared error.

7-Results :

The input-output data set for the neural network training and testing were obtained from experiments in the Nuh Cement Factory. A data set of 455 samples was used to train the neural network model. A data set of 200 samples was utilized to test the network model.

The input and output data were used by the network in the training stage and the network learned the process. After the network was trained, the Fe_2O_3 and Lime Modulus for different combinations of low grade and

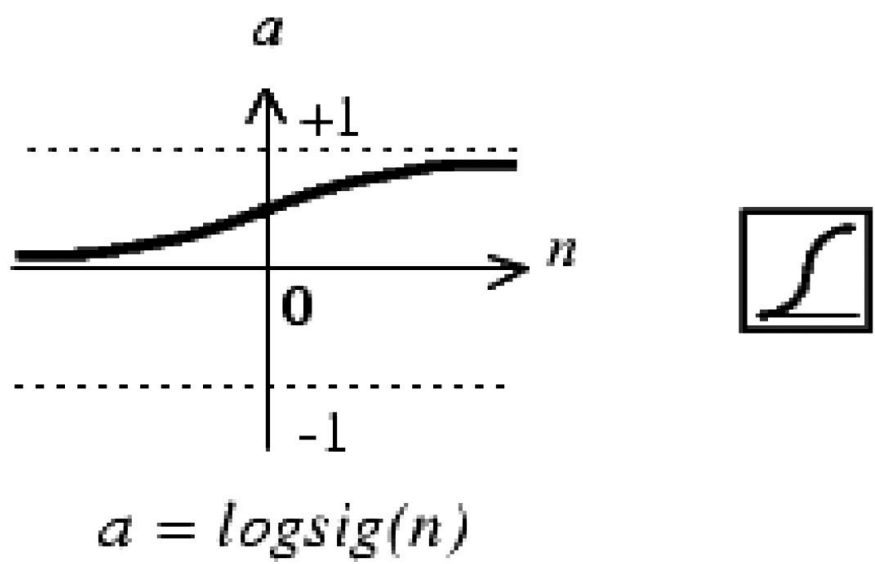


Figure 6: Log-Sigmoid transfer function

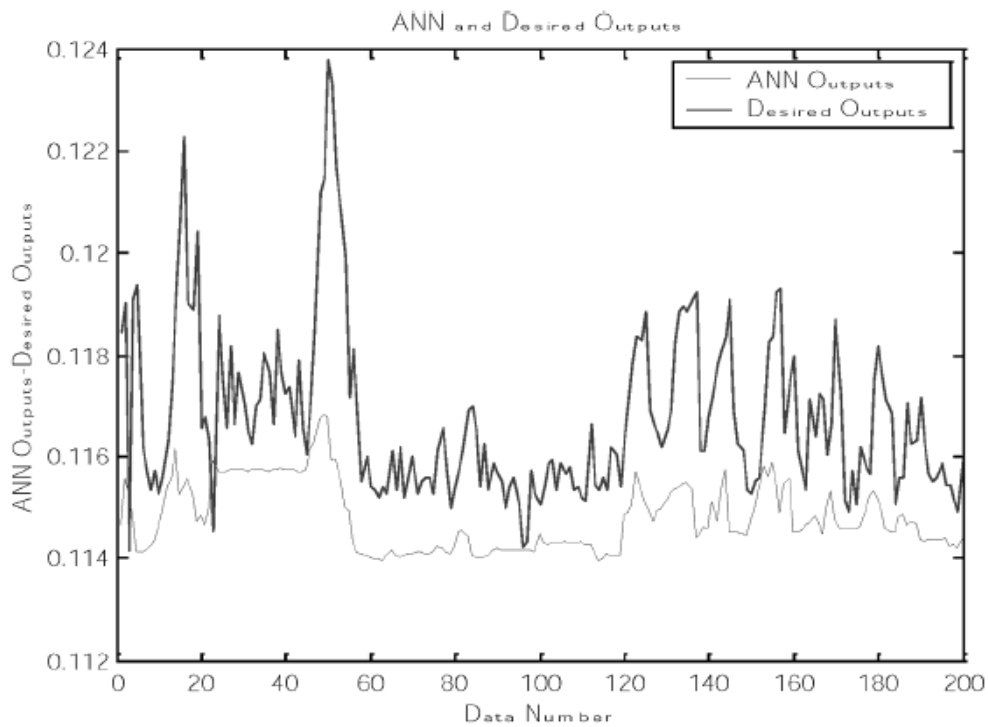


Figure 7: Comparison of the linear neural network prediction with the experimental data (for Fe_2O_3)

iron ore from the test data set were predicted. **Figures 7 and 8** show a comparison of the linear neural network prediction with the experimental data. The comparison of the nonlinear neural network prediction with the experimental data is shown in **Figures 9 and 10**.

During training, the mean squared errors were recomputed using next updated weights and the performance graphic was obtained for nonlinear network in figure 11 the goal in the figures is the target value of the MSE value obtained from the ANN training result as shown in figure 11 the error decreases rapidly in the next iterations.

The Fe_2O_3 prediction of the models indicated that the maximum error between the linear neural network results and desired outputs is about 7.5×10^{-3} and maximum error between nonlinear neural network results and the desired outputs is about 4×10^{-3} . For the Lime Modulus

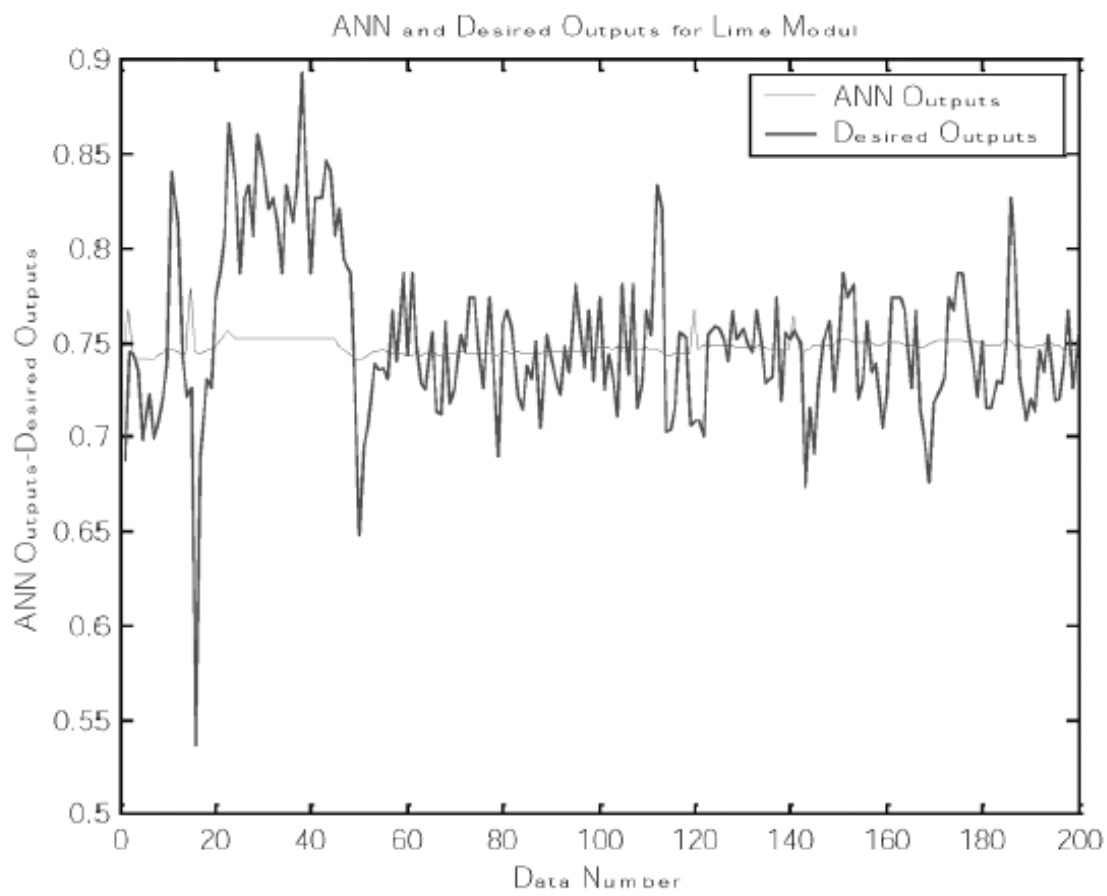


Figure 8: comparison of the linear neural network prediction with experimental data (for lime modulus)

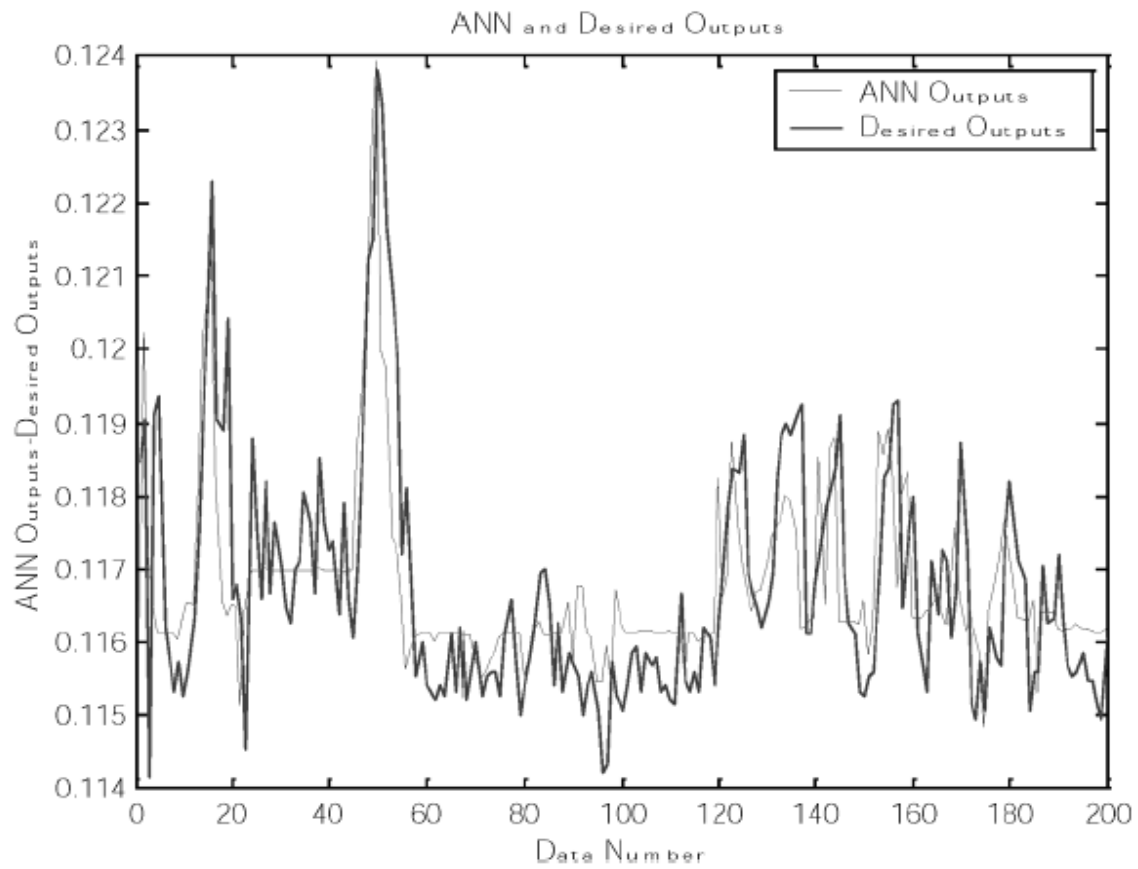


Figure 9: Comparison of the nonlinear neural network prediction with the experimental data (for Fe_2O_3)

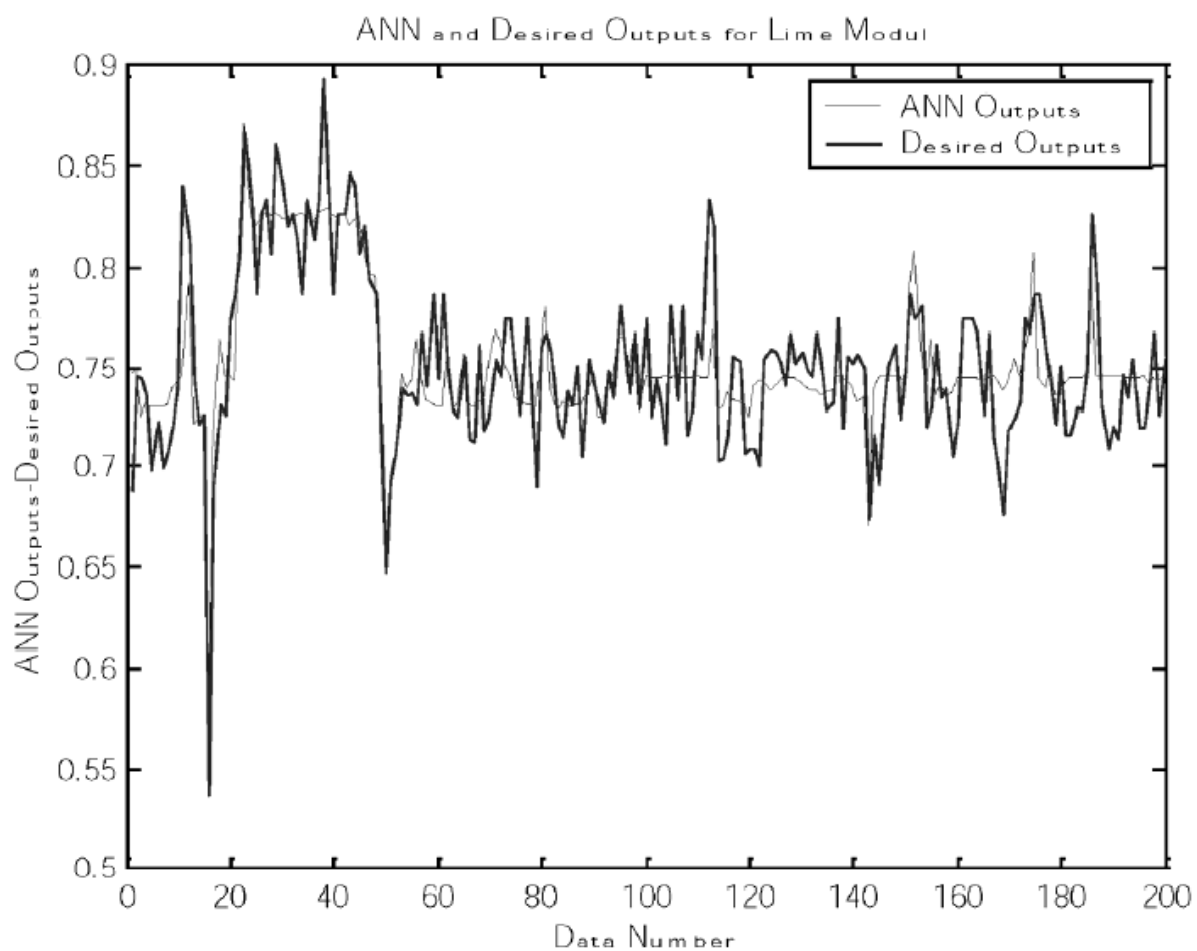


Figure10: Comparison of the nonlinear neural network prediction with the experimental data (for lime modulus)

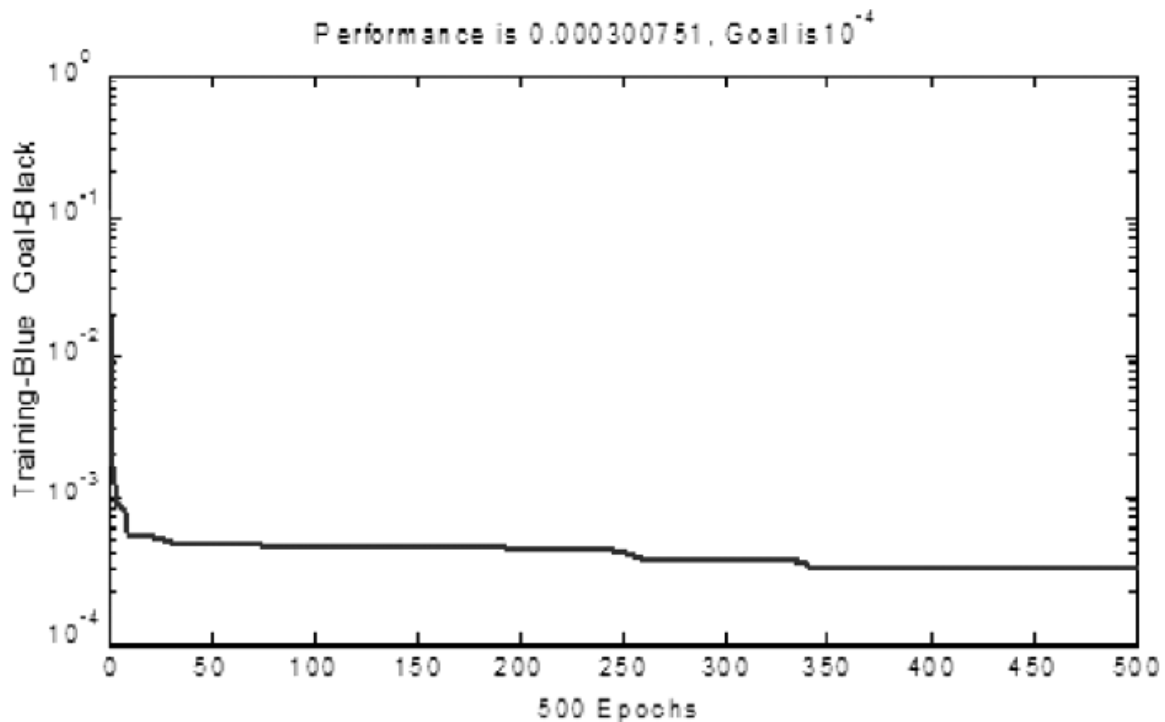


Figure 11: Performance of the nonlinear neural network

output of the models, the maximum error of the linear neural network is about – 0.21 and the maximum error of the nonlinear neural network is about 0.095. Furthermore, the training performance (*MSE*) of the nonlinear neural network reached 3.00751×10^{-4} at 500 epochs. The meaning of the *MSE* being very small is that the desired outputs and the ANN's outputs for the training set have become very close to each other.

8- Cement process in civil optimization:

Cement is an essential constituent of concrete, which is a mixture of cement and coarse and fine aggregate. When mixed with water, this material can be placed in situ or cast in molds (such as concrete blocks). It is a highly versatile building material valued for its high compressive strength, fire resistance, mouldability, impermeability and durability. Mortar (a mix of cement, fine aggregate and water) is used for joining structural blocks, brickwork, and plastering. Both concrete and mortar are vital, and essentially irreplaceable, construction materials for the

building and civil engineering industries. They are widely used in all construction sectors, including house building, road construction, bridges and dams, and in other infrastructure projects, such as railways, airport facilities, hospitals, schools, new offices and shops. Demand for cement is a function of economic activity and construction activity, both of which can be highly cyclical.

9-Evaluation of energy efficiency opportunities of a typical Moroccan cement plant:

The cement industry is one of Morocco's most highly energy intensive economic sectors. It suffers from abnormally high cost of energy supplies, representing more than two thirds of the cost of cement; the first item of expenditure is electricity and fuel with 40% and 30% respectively. Herefor, much more effort is needed to make the cement sector including the optimization of the process reaching energy that saves targets set by the Moroccan energy efficiency strategy. The present work aims to evaluate energy performance of an existing Moroccan cement plant based on a detailed mass and energy balances analysis. Redundant measurements were validated by the Lagrange multipliers technique before being used for the calculation of unmeasured variables. The values for energy consumption and related losses through the whole production line are reported, and the results obtained have been used to assess the energy performance of the process. The evaluation was completed by both an analysis of possible energy loss sources and important solutions described in the international literature to improve the energy efficiency of the entire cement plant in order to assure a well doing and optimizing process .

10-Status of the technology and its future market potential:

The main potential in reducing energy consumption and CO₂ emissions from cement/concrete production is in improvement of cement pyro processing. Pyro processing transforms the raw mix into clinkers. At present, about 78% of Europe's cement production is from dry process kilns, a further 16% of production is accounted for by semi-dry and semi-wet process kilns, with the remainder of European production, about 6%, coming from wet process kilns. The wet process kilns operating in Europe are generally expected to be converted to dry process kiln systems when renewed, as are semi-dry and semi-wet processes kiln systems. On average, pyro processing systems in the EU and US operate at below 35% thermal efficiency, which is rather low. The percentage is even lower for developing countries. These process improvements will come from better energy

management, upgrading existing equipment (e.g. replacing wet kilns, upgrading to preheater and precalciners), adopting new pyro processing technologies (e.g. fluidized bed systems) and, in the longer term, performing the R&D necessary to develop new concepts for the cement manufacturing processes.

11- CONCLUSION :

In this project the raw-material blending process in a cement factory was examined and two different mathematical models were developed using linear and nonlinear neural networks. In this modeling the experimental data were used from a controlled process under varying operating conditions in the Nuh Cement Factory in Turkey. Good parametric multivariable models having the minimum number of parameters were obtained. The inputs are the feed ratios of the raw materials (low grade and iron ore) and the outputs are iron oxide and/or the lime module values of the raw meal.

The developed linear and nonlinear neural network predictions were compared with the experimental results. The network test showed that the nonlinear neural network has a higher predictive accuracy and convergence for the raw-material blending process. The linear model-based prediction shows a greater deviation than the nonlinear model. The mathematical model that is established by the nonlinear neural network is a suitable model for the blending process of cement raw material.

Finally, this multi-input, multi-output model has made possible the control of the iron oxide and the lime module together, instead of using parallel-working single-loop controllers. In this case only the lime module or the iron oxide could have been controlled, depending on the choice in the Nuh Cement Factory with the available control package, designed models give the opportunity for these outputs to be controlled together by using a two-input, two-output process model. Furthermore, stable operating conditions can predict the process with these models.

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